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The impact of credit conditions on market liquidity – a case for European stock markets

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Abstract

The recent financial crisis has drawn the attention of researchers and regulators to the importance of liquidity for stock market stability and efficiency. The ability of market-makers and investors to provide liquidity is constrained by the willingness of financial institutions to supply funding capital. This paper sheds light on the liquidity linkages between the Central Bank, Monetary Financial Institutions and market-makers as crucial elements to the well-functioning of markets. Results suggest the existence of causality between credit conditions and stock market liquidity for the Eurozone between 2003 and 2015. Similar evidence is found for the UK during the post-crisis period.

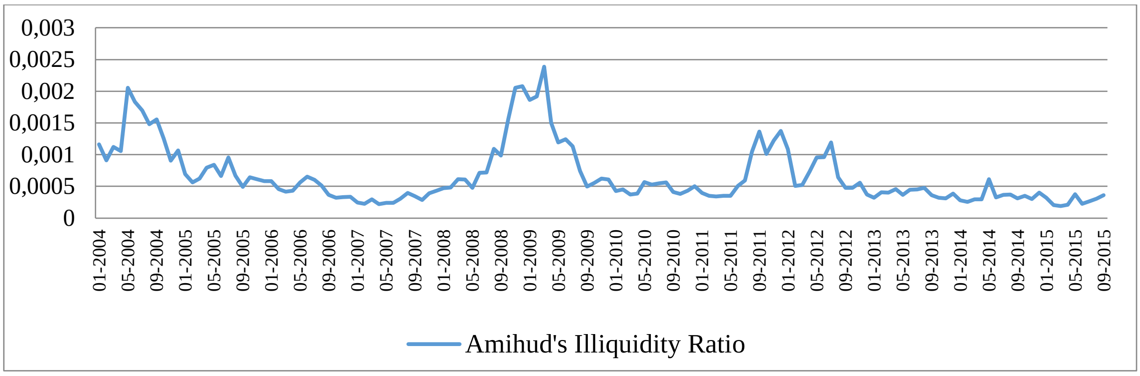
Keywords: stock liquidity, credit conditions, monetary policy, Eurozone

1. Motivation

“Liquidity is the lifeblood of financial markets”[1]. It is a complex and multi-faceted concept. Though widely recognized, to the present, neither a generalized definition of liquidity nor a single measure capturing all its dimensions has become unanimously accepted. Nevertheless, a common ground point is that liquidity reflects the easiness of realizing transactions between agents within the financial system. Hence, liquidity risk arises from the fact that, in equilibrium, individuals prefer to have liquidity combined with the possibility of not being liquid at some point in time.

The recent financial crisis has highlighted the importance of liquidity as a precondition for market completeness. Historically, market liquidity risk has been stable and persistent, though the occurrence of rare and episodic events revealed the inelasticity of liquidity supply during crisis. This sudden liquidity “dry-up” may cause large falls in asset prices, not explained by changes in the fundamentals, and augmented by downward spirals: fire sales and deleveraging as means to meet capital ratios and margin calls.

Graph 1 – Eurozone’s Amihud Illiquidity Ratio[2]



Graph 1 exhibits the Amihud (2002) illiquidity ratio for the Eurozone[3] and clearly illustrates the aforementioned illiquidity spikes for 2008-2009 and 2011-2012, precisely the periods following the financial and the European sovereign debt crisis, respectively.

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[1] See Fernandez, F. A. (1999), Liquidity risk. SIA Working Paper

[2] Measures the elasticity of stock prices relatively to trading activity, further detail in Section 3

[3] For an overall index of four stock market indices: DAX, CAC 40, FTSE MIB and AEX

Market liquidity influences a diverse spectrum of macroeconomic indicators as well as the decision-making of both firms and investors. Næs et al. (2011) evidence that stock market liquidity is positively correlated with current and future economic growth rates and a robust predictor of several macroeconomic aggregates. At the firm level, Khapko (2009) concluded that firms with less liquid stocks tend to have higher debt ratios and are less likely to issue equity. Amihud and Mendelson (1986) and Pastor and Stambaugh (2003) prove the existence of a liquidity risk premium for holding illiquid stocks, controlled for other risk factors.

The global financial crisis of 2007-08 has changed the paradigm for the entire financial system, with consequences for stock market liquidity. Central banks have developed accommodative policies, through liquidity emergency programs, reduction of policy rates and the expansion of monetary bases, loan provision to banks or asset purchase programs (quantitative easing). Initially aimed at reducing financial market distress, these policies also attempted to stimulate the real economy, although the effects at broad monetary aggregates were residual since banks preferred to hold reserves. Facing rating downgrades, banks had to deleverage to comply with higher capital standards and lowered the access to funding to investors. The current market microstructure is characterized by fragmented large trades, less structured products, increasing electronic trading and more high-frequency traders, which reduce transaction costs but still fail to supply liquidity during turmoil periods.

This paper aims to examine the theoretical and empirical relationship between the Eurozone's overall credit conditions – the willingness to provide funding liquidity to market intervenients - and stock market liquidity. Credit conditions are assumed to be driven by the monetary policy stance and resultant interbank market dynamics, changes in monetary and credit aggregates, as well as the Monetary Financial Institutions (MFIs) balance sheet size and composition.

2. Literature Review

The literature on stock market liquidity is extensive. Nevertheless, only very recently studies have investigated the liquidity linkages within the financial intermediation chain, mainly the existence of feedback mechanisms, as well as spillover effects from monetary policy and funding liquidity. This section briefly describes the existing literature on stock market liquidity and details the interactions between drivers of overall credit conditions and stock market liquidity dimensions.

According to Lybek and Sarr (2002), liquid markets tend to display five distinct and complementary characteristics: tightness; immediacy; depth; breadth and resiliency. Tightness gives respect to low transaction costs, while immediacy defines the speed or order execution, together with the efficiency of trading, clearing and settlement systems. Depth refers to the existence of abundant orders, below the security price. Breadth means that orders are numerous and large in volume, with minimal impact on prices. A market is said to be resilient if new orders flow quickly to order imbalances and attenuate price movements away from fundamentals.

In a different perspective, some studies have attempted to validate theoretical properties generally associated with market liquidity. First, commonality in liquidity outlines the fact that exogenous shocks simultaneously affect all securities in a given market and across markets, representing a level effect. Further, the "flight-to-quality" effect reports investment allocation changes from small to large caps or ultimately from stocks to bonds, since shocks are more prone to affect securities with higher volatility, indicating a slope effect. Asymmetry gives respect to the non-linear response of some liquidity dynamics to exterior innovations, which are more informative when the risk level is already high. Finally, recall that liquidity appears to be inelastic in the short-run and is intrinsically related to volatility. Brunnermeier and Pedersen (2009) developed an equilibrium model in which market and funding liquidity are mutually reinforcing and sustained by these propositions. Consistent with the latter predictions, Fontaine and Garcia (2015) observe these same properties for the NYSE, from 1986 to 2012.

Since the genesis of financial markets, intermediaries such as brokers and dealers, hedge funds and other liquidity suppliers have played a crucial role for market completeness and the allocation of capital across financial assets. Provided the intermediaries' wealth is limited, their willingness to provide liquidity will necessarily depend on their ability to obtain funding. Moreover, funding risk and shocks are contingent on the *status quo* of credit conditions. Gromb and Vayanos (2010) document that market liquidity depends on intermediary capital, namely on the collateral-based financial constraints that limit investment capacity. Likewise, Johnson (2009) argued about the importance of the stock of liquid capital to accommodate trade demands and to adjust consumption as a determinant of market resiliency. Further, Valente (2010) underlines the existence of two extreme regimes: a binding regime in which funding and market liquidity are positively correlated, and a non-binding regime without any evidence of correlation, reaffirming the asymmetry property. Adrian and Shin (2010) describe how intermediaries adjust balance sheets and leverage through repurchase agreements, so as the direct impact of funding conditions to asset prices and liquidity.

In the Eurozone, the dynamics between credit conditions and market liquidity are defined by specific interactions and responsibilities assigned to institutions, intermediaries and investors. Nikolaou (2009) distinguishes between three liquidity types. First, central bank liquidity, provided by the ECB, is measured by narrow money M1[4]. Second, funding liquidity is simply the ability of banks to meet their liabilities and to raise funding in short notice. The

[4] Following the ECB notation, equal to currency in circulation plus overnight deposits within the ECB

liquidity sources of MFIs are deposits, the ECB, the interbank market and the asset market. Third, the characterization of market liquidity is similar to previous mentioned findings.

Liquidity linkages amongst all types enhance the smooth functioning of the financial system during normal times, but also represent propagation channels of liquidity risk during turbulent periods. In fact, a virtuous circle stimulates liquidity flows easily during stable periods. The ECB, monopoly-provider of liquidity, supplies the liquidity amount that brings interbank and policy interest rates into equilibrium. Subsequently, liquidity is received by banks and redistributed accordingly through interbank and asset markets to liquidity-needing agents. Finally, financially constrained agents demand the necessary amount of liquidity to satisfy funding necessities, generating a new aggregate liquidity demand to banks and to the ECB and a new circle begins.

On the opposite, coordination failures among depositors, banks and intermediaries fed by asymmetric information and incomplete markets, create a vicious illiquidity spiral in the system. The fragile nature of banks derived from balance sheet maturity mismatch allied to fears of counterparty credit risk, deposit withdrawals, and ultimately bank runs trigger a liquidity shortage and the impairment of the interbank market. To avoid liquidation costs, banks restructure portfolios and enter in fire sales of distressed assets, aggravated by trading frictions. As in Brunnermeier and Pedersen (2009), the liquidity spiral continues with the gradual decrease in asset prices and net worth of investors, forcing to further leverage adjustments in order to meet solvency constraints. Instead, the asset market could have caused the downward spiral. In response to falling asset prices, investors reduce positions, leading to higher transaction costs and losses on existing positions, exacerbating funding risk.

Several studies corroborate the existence of such mechanisms in practice. Gagnon and Gimet (2013) evidence a positive impact on funding and market liquidity following a decrease in the policy rate. Also, Fernández-Amador et al. (2013) conclude that the EONIA and monetary base growth Granger-cause stock market liquidity, while evidence for a reversed relationship is weak. Chordia et al. (2005) report the monetary policy stance, in the form of net borrowed reserves, as a driver of stock market liquidity. On the contrary, Chatterjee (2015) finds evidence that asset market liquidity explains the liquidity creation of large banks.

Given these points, there is a compelling evidence to assume that the activity of both the ECB and MFIs is an important factor to determine credit conditions in the Eurozone. Considering this, it is relevant to assess the decision-making evolution of both intervenients in the context of pre and post-crisis periods. Until 2008, the ECB has only used conventional policy instruments. Following the 2008 financial collapse, it has enacted credit support to financial institutions, several asset purchase programs and, more recently, its first quantitative easing (QE) program. Nevertheless, the decline in the money multiplier illustrates the ineffectiveness of monetary policy, particularly relevant when interest rates are at the zero-lower bound (Valiante, 2015). Most liquidity injected in the financial system has been accumulated in the form of reserves and in the deposit facility.

Conversely, banks funding practices have also changed in the last decade. In detail, the recourse to non-core liabilities (i.e. liabilities other than retail deposits) and the ongoing growth of the outstanding amounts of equity funds units demonstrate the maturation of the capital-market based "shadow" banking model.

This study contributes to the existing literature by investigating the joint dynamics of the ECB and MFIs actions on the funding provision to intermediaries and investors, particularly their subsequent impact on stock market liquidity. Furthermore, the long time span considers a period of transversal changes for the European financial system. The purpose of this project disregards the microstructure characteristics of all trading systems considered, as well as country regulatory and accounting frameworks.

3. Methodology & Results

In order to accurately describe the dynamics between credit conditions and stock market liquidity, it is relevant to consider the aforementioned liquidity spirals, potential sources of endogeneity in the system. Provided there are reasons to expect bidirectional causalities, this relationship is examined by specifying a Vector Autoregressive (VAR) model. By their linear structure, VAR models became popular after Sims (1980) proposed them as an improvement to models with simultaneous equations, and have empirically proven to provide superior forecasts for macroeconomic and financial time series. However, VAR pitfalls arise in terms of parsimony, stationarity issues and coefficient interpretation.

To pursue this analysis, four of the most developed European stock markets were considered, particularly Germany, France, Italy and the Netherlands. The sample includes a total of 104 stocks included in the actual composition of the DAX, CAC 40, FTSE MIB and AEX stock indices, respectively. Stocks with non-available data or presenting discontinuous and outlier values were not considered. All data was retrieved from Bloomberg, the ECB Statistical Data Warehouse and the Eurostat. The sample period starts in January 2003 and ends in September 2015, a total of 153 months. In this sense, it is attempted to encompass different macroeconomic and financial cycles, while avoiding an eventual structural break with the introduction of the euro in 1999 and less frequent observations for stock market liquidity variables until the end of 2002.

3.1 Stock Market Liquidity Variables

As pointed in the previous section, instead of reaching a unanimous single-measure and definition of stock market liquidity, past literature defined a set of characteristics a liquid asset or market must necessarily exhibit. Combining the research of Lybek and Sarr (2002) and Nikolaou (2009), three categories of measures were considered: volume-based, price-impact costs and transaction costs. Notwithstanding, one should account that all categories are inter-connected and do not incorporate qualitative factors such as market microstructure, legislative frameworks, payment risks and settlement systems.

First, a volume-based measure is mostly informative about trading activity and concerns market breadth and depth. Amihud and Mendelson (1986) stated that, in equilibrium, liquid stocks should be traded more frequently, since the costs of holding illiquid assets could optimally be spread for longer periods. In this sense, Datar et al. (1998) propose the turnover rate (TO) measure as a proxy for trading activity. The daily turnover rate of stock i is computed by dividing the daily number of shares traded by the number of shares outstanding.

$$TO_{i,day} = \frac{\#\, shares\ traded_{i,day}}{\#\, shares\ outstanding_{i,day}} \times 100 \qquad (1)$$

Second, indicators of price-impact costs aim to assess market resiliency and speed of price discovery. Particularly, they capture the price responsiveness to order flow movements since, intuitively, more liquid assets should be less sensitive to large and numerous orders. Orderly and resilient markets provide greater price continuity and lower volatility, key indicators of liquidity and critical for investment decision-making. The Amihud's (2002) illiquidity ratio (AMIHUD) ascertains an elasticity dimension of liquidity, that is, the response of returns to 1 euro of trading volume. Despite being highly correlated with market capitalization and inflation, many researchers advocate its adequacy as a price impact measure. Contrary to the turnover rate, this measure is negatively related to liquidity and given by the ratio between the absolute daily return of stock i divided by the respective traded value in euro.

$$AMIHUD_{i,day} = \frac{|Return_{i,day}|}{Traded\ value\ in\ euro_{i,day}} \times 10^6 \qquad (2)$$

Third, transaction costs may be viewed as the price required by market-makers (brokers and dealers) for providing liquidity services and immediacy of execution, thus representing the cost of liquidity. In this context, the Amihud and Mendelson (1986) relative bid-ask spread (BID_ASK) is the most widely used measure. The spread depicts the sum of the buying premium and the selling concession and is computed as the ratio of the difference between the daily ask and bid price to the last price.

$$BID\_ASK_{i,day} = \frac{Ask-price_{i,day} - Bid-price_{i,day}}{Last-price_{i,day}} \times 2 \tag{3}$$

A preliminary analysis to the daily data for market liquidity measures exposed several anomalous and extreme values which could undermine the final results. Hence, for each stock index two filters were applied by deleting daily index indicators formed by less than 10 observations of individual stocks and months with less than 10 trading days available were also removed. To aggregate each liquidity measure (MLIQ), the daily average of the liquidity measure for all individual stocks in the index is computed[5]. Finally, daily figures are equally-averaged to obtain monthly-level indicators[6], which subsequently are aggregated to an overall level by estimating a weighted average using the number of stocks corresponding to each index as the weights assigned[7].

3.2 Credit Conditions Variables

Similarly, credit conditions cannot be assessed based on a single indicator. Instead, three major factors are considered: interbank market credit risk, the monetary policy effectiveness to stimulate credit creation, and the composition of bank liabilities.

The interbank market is undoubtedly the major source of liquidity for MFIs. In this sense, a measure of the perceived risk and creditworthiness in this market may provide an accurate proxy of funding liquidity. As suggested by Brunnermeier (2009), market observers often focus on the TED spread, the difference between the 3-month U.S dollar LIBOR[8] and

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[5] $MLIQ_{index,day} = \frac{1}{\#\, stocks_{index,day}} \times \sum MLIQ_{stock,day}\,, for\ stock = 1, \dots, \#stocks\ \wedge\ \#stocks \geq 10$

[6] $MLIQ_{index,month} = \frac{1}{\#\, trading\ days_{index,month}} \times \sum MLIQ_{index,day}\,, for\ day = 1, \dots, \#trading\ days\ \wedge$ $\#trading\ days\ \geq 10$

[7] $MLIQ_{overall,month} = \frac{1}{\#\, stocks_{overall,month}} \times \sum \left(MLIQ_{index,month} \times \#stocks_{index,month}\right), for\ index = 1, 2, 3, 4$

[8] London Intebank Offered Rate

the 3-month U.S Treasury Bills rate. The spread measures the difference in yields between unsecured top-rated interbank loans and government seemingly ‘riskless’ credits, though after the financial crisis researchers often disagree on its definition and content. Although both rates tend to co-move, a TED spread widening is characteristic of a destabilizing spiral predictor, impacting both interbank liquidity and credit availability. To estimate the Eurozone analogous TED spread (TED_EZ), the difference between the 3-month Euribor[9] and the 3-month zero-coupon German bund is computed. The German bund is frequently used as the risk-free rate benchmark for the Eurozone.

$$TED\_EZ_{month} = 3M\ EURIBOR_{month} - 3M\ German\ Bund_{month} \qquad (4)$$

The volume of money supply is the result of the transmission mechanism interaction between the central bank, the banking sector and non-financial intermediaries. In particular, money creation is ultimately linked to credit expansion and to the intermediation capacity of MFIs through the credit-deposit multiplier process.

A traditional method to assess the monetary policy effectiveness and credit development is through the money multiplier approach, which presumes that broad money M3 is solely driven by narrow money M1 and the money multiplier (MM). Nonetheless, this proposition assumes that the behaviour of banks and the money-holding sector will respond in a predictable way to shocks in M1. By contrast, after 2008, in the context of extreme uncertainty regarding bank balance sheet soundness in the interbank markets, banks responded to the ECB liquidity stimuli by increasing reserve holdings beyond the minimum requirement. To demonstrate this point, it may be interesting to analyse the decomposition of the money multiplier:

$$Money\ Multiplier = \frac{1+\frac{C}{D}}{\frac{R}{D}+\frac{C}{D}} \qquad (5)$$

[9] Euro Interbank Offered Rate - the rate at which a prime bank within the EU interbank market is willing to lend funds in euro to another prime bank. Several financial products are indexed to this rate.

Where C/D is the currency-to-deposits ratio (CUR_DEP) and R/D the reserves-to-deposits ratio (RES_DEP)[10].

As can be derived, changes in MM are negatively driven by increases in the currency-to-deposits ratio and in the reserves-to-deposits ratio. Intuitively, if currency holders retain more money as currency and banks hold more reserves, the multiplier effect through loans and deposits is reduced. Positive innovations in the reserves-to-deposits ratio underpin that MFIs are less willing to provide funding liquidity. On the other hand, the currency-to-deposits ratio may signal a twofold effect on stock market liquidity. The decision to hold currency instead of depositing or investing can be either caused by good credit conditions in the form of very-low interest rates or by a higher perception of risk and preference for liquidity. In short, both components of MM are included in the model to retain the informative power of both variables for coherence.

At last, credit availability may be associated to the MFIs balance sheet size and composition not scrutinized by monetary aggregates. In a bank-based economy, MFIs are the most important financial intermediaries to which retail deposits (core liabilities) have been the main source of funding. Nonetheless, Hahm et al. (2013) report that whenever credit is growing at a faster pace compared to deposit levels, banks turn to other funding sources. For this reason, the amount of MFI non-core liabilities is a prime indicator of higher credit availability and inherent lower external finance premiums, necessary conditions for easing credit conditions.

The current systematic low-margin banking environment is leading to gradual deleveraging, thus benefiting the capital-market banking model. Namely, the on-going rise of the asset management activity in Europe has posed a good source of collateral for the repo

[10] C denotes banknotes in circulation, D denotes deposits in M3 (overnight deposits + deposits up to 2 years + deposits redeemable up to 3 months + deposits up to 2 years and redeemable up to 3 months) and R represents credit institutions' reserves (ECB credit institutions current account + ECB deposit facility)

markets, key funding instruments for market-makers. All in all, to consider the impact of both factors for overall credit conditions, a final variable is included:

$$NCORE_{month} = ln\left(Non - core\ liab._{month}{}^{11} + Equity\ fund\ shares/units_{month}\right) \qquad (6)$$

Where ln represents the natural logarithm and Non-core liab. the outstanding amount of MFIs non-core liabilities to which the outstanding amount of equity and non-money-market funds shares/ units is added.

3.3 Adjustment of Time Series

3.3.1 Control Variables

As mentioned, the relationship between stock market liquidity and main financial and macroeconomic indicators has been thoroughly documented. Under those circumstances, failing to control for these exogenous factors may lead to inconsistent results. Thus, following Chordia et al. (2005), the weighted-average of monthly returns (MRET) and monthly standard deviation of daily stock returns (MSTDEV) are introduced, again considering the number of stocks as weights allocated to each stock index. Since the short-term business cycle and price evolution developments also represent crucial information criteria for the ECB, the annual rate of change of the Euro Area Harmonised Index of Consumer Prices (IR)[12] as a proxy for inflation and the Euro Area Industrial Production Index (IPI)[13] are included. All four indicators are incorporated as exogenous variables.

3.3.2 Stationarity Tests

According to Lütkepohl (2005) every stationary, strictly non-deterministic process can be approximated by a VAR model. For this reason, dealing with non-stationary variables may result in spurious regressions, inconsistent estimators and subjacent incorrect causality test-statistics. Provided this, to ensure that all variables are stationary and of the same order of

[11] Non-core liabilities = debt securities held + money market funds shares/ units + debt securities issued + remaining liabilities + external liabilities, extra Euro Area

[12] Euro Area actual composition (19 countries)

[13] Measures changes in output and activity of the industry sector excluding construction (NACE Rev.2, Eurostat) on a monthly basis, current base year is 2010 (Index 2010 = 100) and Euro Area actual composition (19 countries)

integration, Augmented Dickey-Fuller (ADF) tests[14] were performed for all variables. Only for the currency-to-deposits ratio (CUR_DEP) and the inflation rate (IR), the null hypothesis of a unit root was not rejected at a 5% significance level. Therefore, first differences of both indicators were taken, dCUR_DEP and dIR, respectively.

3.4 Descriptive Statistics and Correlation Matrix

Table 2 presents summary statistics for all variables during the entire period covered by the sample. As projected, the time interval considered for this analysis comprises different financial and business cycles, emphasized by disperse values observed in the TED spread, monthly stock returns and in the industrial production index.

Likewise, Table 3 shows pairwise correlation coefficients between all variables. The high negative correlation between non-core liabilities and the Amihud's ratio indicates that the first may perhaps be a good estimator of the latter. Also, the market standard deviation is positively correlated with the turnover rate, the Amihud's ratio and the TED spread, meaning that these variables could indicate market's perception of increasing risk.

3.5 Model Specification and Validation

Accordingly, the following VAR model of order p is specified:

$$y_t = AY_{t-1} + B_0 x_t + u_t{}^{15} \qquad (7)$$

The procedure to select the optimal lag length must contemplate the consistency of the estimators and guarantee that innovations follow a White Noise process. Ultimately, it is implausible to satisfy both criteria simultaneously and avoid the trade-offs involved in this decision. For this purpose, the Akaike (AIC) and the Schwarz-Bayesian information criterion (BIC) were estimated from lags 1 to 5[16]. The lag length that minimizes the AIC is 4 whilst the BIC is optimal for order 1, in line with the more conservative approach of the first measure.

[14] ADF test results are presented in Table 4 of the Appendix

[15] y_t is a vector of the 7 endogenous variables (TO, AMIHUD, BID_ASK, TED_EZ, dCUR_DEP, RES_DEP and logNCORE); A is a matrix of coefficients for endogenous variables; Y_{t-1} is a matrix of past values of all endogenous variables; B_0 a matrix of coefficients for exogenous variables and the constant term; x_t a vector of exogenous variables and a constant term; and u_t a vector of residuals

[16] Results reported in Table 5 of the Appendix

As means to retain a simpler and more parsimonious structure, a VAR (1) model is therefore chosen.

Nevertheless, in order to secure the whiteness of model residuals, the Lagrange-Multiplier (LM) test was performed for the null hypothesis of no residual autocorrelation of order 1 and rejected at a 5% significance level. To repeat the test in an ascending order, one more lag is added to the VAR model[17]. The test sequence was terminated at the lag length of 4, for which the null of no residual autocorrelation was not rejected. In short, specifying a VAR (4) model satisfies the AIC and retains the asymptotic properties of the estimators.

Before performing causality and structural analyses of the VAR model, the initial assumption of stability must be validated. Lutkepohl (2005) states that a VAR model of order p is stable if all eigenvalues of the A coefficient matrix have no roots within or on the unit circle, meaning that impulse response functions (IRFs) have known interpretations. After performing the test[18], the results conclude that all the eigenvalues lie inside the unit circle, thus the referred VAR model is stable.

3.6 Causality Analysis – Granger-causality tests

To interpret the results of the estimated VAR (4) model, Granger-causality tests[19] are conducted to assess the existence of a statistically significant impact of credit conditions on stock market liquidity and vice-versa. This concept advocates that if variable x Granger-causes variable y, then past values of x contain information to improve the estimates of y beyond past values of y alone. The null hypothesis states that the credit conditions (market liquidity) variable does not Granger-cause the market liquidity (credit conditions) variable. Table 1 reports Chi-square test-statistics and p-values for all the tests, divided by the two possible directions of causality.

[17] Results of the LM Test are presented in Table 6 of the Appendix
[18] Results presented in the Annex
[19] See Granger (1969) and Sims (1980)

Table 1 – Granger-causality Tests

All data considered in the sample was retrieved from Bloomberg, the ECB Statistical Data Warehouse and the Eurostat from January 2003 to September 2015. Market liquidity variables included observations from 104 stocks currently traded in the DAX, CAC 40, FTSE MIB and AEX stock indices. Stocks with non-available data or presenting anomalous values were not considered.

Credit Conditions	Market Liquidity		
	TO	AMIHUD	BID_ASK
(i) – Credit Conditions (row) → Market Liquidity (column) H_0: Credit Conditions measure (row) does not Granger-cause the Market Liquidity measure (column)			
TED_EZ	15.612*** (0.004)	1.080 (0.897)	12.579** (0.014)
dCUR_DEP	12.024** (0.017)	51.723*** (0.000)	5.900 (0.207)
RES_DEP	6.057 (0.195)	4.782 (0.310)	16.671*** (0.002)
logNCORE	13.466*** (0.009)	9.800** (0.044)	2.480 (0.649)
(ii) – Market Liquidity (column) → Credit Conditions (row) H_0: Market Liquidity measure (column) does not Granger-cause the Credit Conditions measure (row)			
TED_EZ	5.602 (0.231)	8.038* (0.090)	4.194 (0.380)
dCUR_DEP	5.487 (0.241)	36.644*** (0.000)	4.764 (0.312)
RES_DEP	2.389 (0.665)	6.409 (0.171)	93.843*** (0.000)
logNCORE	5.380 (0.250)	5.912 (0.206)	3.186 (0.527)

Note: P-values in parenthesis. *, ** and *** denote 10%, 5% and 1% significance levels

Overall, the results of the Granger-causality tests corroborate that credit conditions Granger-cause market liquidity in all its three dimensions. Apart from certain exceptions, there is little evidence of a bidirectional causal relationship. In detail, the TED spread for the Eurozone, the currency-to-deposits ratio and the non-core liabilities of MFIs seem to be informative to predict simultaneously two market liquidity variables, whereas the reserves-to-deposits ratio only has a statistically significant impact on the bid-ask spread. Conversely, the Amihud's illiquidity ratio and the bid-ask spread Granger-cause the currency-to-deposits and the reserves-to-deposits ratios, respectively.

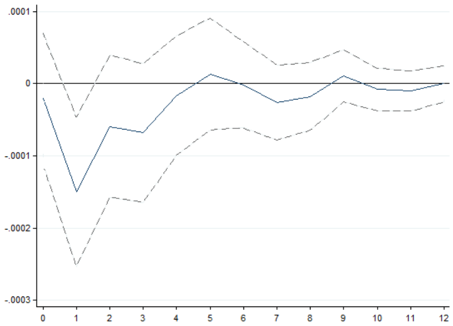
3.7 Structural Analysis – Impulse Response Functions

The causality analysis provided by the Granger-causality tests does not tell the entire story about the interactions between the variables. As results are based on single equation coefficients, they do not consider the joint dynamics in the VAR system. Hence, a clearer picture can potentially emerge by the use of IRFs. The IRFs represent the impact of a one-time, unit standard deviation, positive shock to the impulse variable on the present and future values of the response variable in a higher dimensional system.

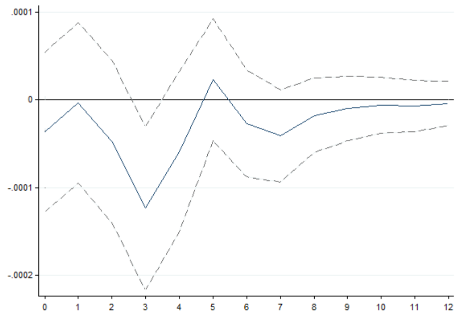
Before conducting this procedure, some key issues must be addressed. First, Luktepohl (2005) asserts that IRFs are not statistically different from 0 if the impulse variable does not Granger-cause the response variable. Second, IRFs assume that a shock occurs only in one variable at a time. In order to ensure that shocks and independent, residuals are orthogonalized by a Cholesky decomposition. At last, the accuracy of results is sensitive to the ordering of variables in the VAR estimation. The Wold causal ordering determines that variables with greater transversal influence should be placed first. Following Fernández-Amador et al. (2013), monetary and credit variables are placed before market liquidity indicators.

Graphs 2-10 depict the one Cholesky standard deviation innovation impact on the response variable of interest for all significant Granger-causality interactions[20].

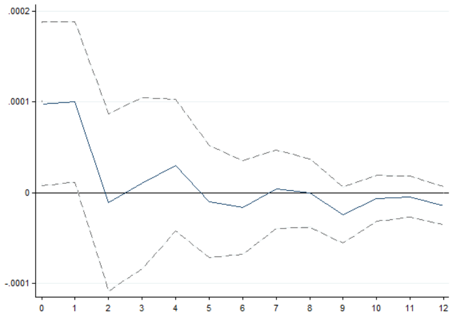
Graph 2 – Response of TO to TED_EZ



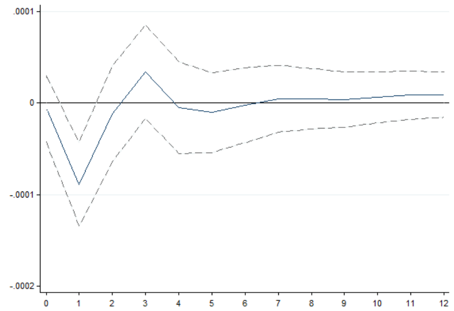
Graph 3 – Response of TO to dCUR_DEP



Graph 4 – Response of TO to logNCORE



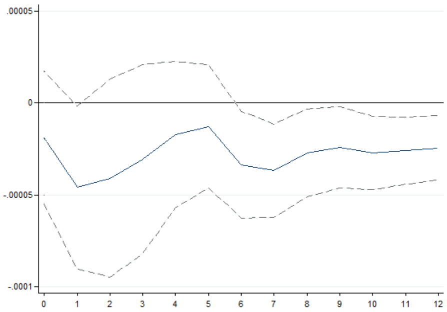
Graph 5 – Response of AMIHUD to dCUR_DEP



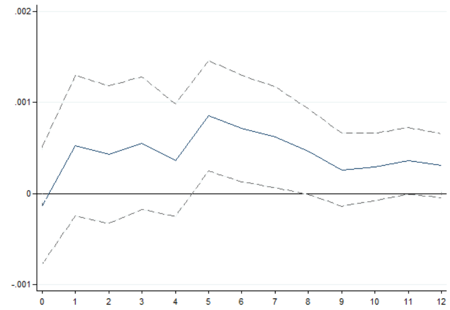
Legend: Orthogonalized IRF 95% Confidence Interval Bands

[20] The remaining IRFs are presented in the Annex

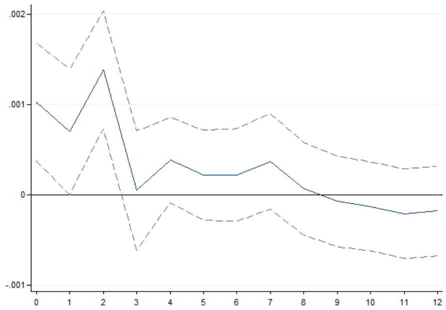
Graph 6 – Response of AMIHUD to logNCORE



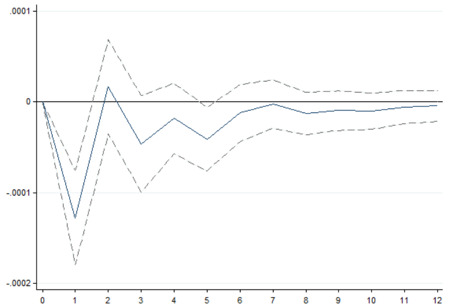
Graph 7 – Response of BID_ASK to TED_EZ



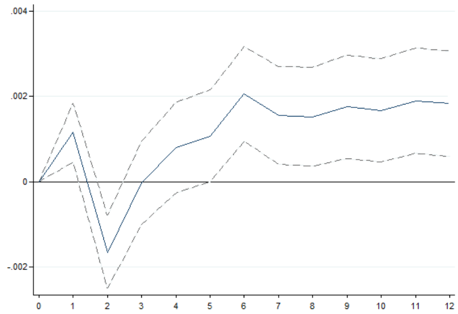
Graph 8 – Response of BID_ASK to RES_DEP



Graph 9 – Response of dCUR_DEP to AMIHUD



Graph 10 – Response of RES_DEP to BID_ASK



Legend: Orthogonalized IRF 95% Confidence Interval Bands

Overall, the IRF results are the empirical reflex of the financial theory and emphasize how changes in several aspects of credit conditions directly impact various dimensions of stock market liquidity. With certain exceptions, the impact of explanatory variables is only significant in the short-term, mainly on the first 3 months.

Additionally, the signs of all IRFs confirm the hypotheses presented in previous sections. The TED spread has a negative effect on the turnover rate, while at the same time a positive effect on the bid-ask spread after a few months, hence positive shocks to this variable exercise a negative influence on market liquidity. As predicted, the currency-to-deposits has a dual effect: negative on the turnover rate, lowering trading activity and positive to reduce price impact costs hereby represented by the Amihud's illiquidity ratio. Further, the bid-ask spread response to a shock in the reserves-to-deposits ratio is positive, proving that if MFIs retain higher reserves intermediaries will have lower funding liquidity and therefore reduce their market-making activity. Moreover, increasing non-core liabilities significantly raises the turnover rate on the short-term, though has a lasting and structural effect on reducing the Amihud ratio. The latter result may indicate that financial intermediaries and investors do not have an immediate reaction to this variable, but instead tend to wait to adjust their balance sheets and funding constraints. Lastly, positive innovations in the Amihud ratio and the bid-ask spread have a positive impact on the money multiplier, by reducing the currency-to-deposits and the reserves-to-deposits ratios, respectively. This bidirectional causality effect proves the existence of a liquidity spiral only extended to the money multiplier level.

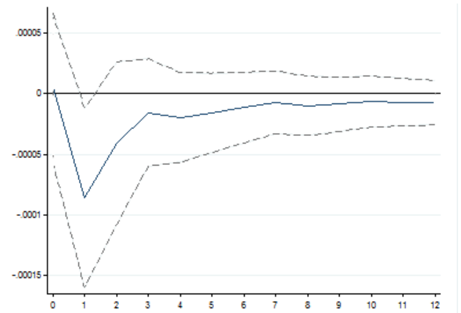
3.8 Robustness Check – a similar model for the United Kingdom

The aforementioned results are cemented on liquidity interactions within the bank-based financing structure of the Eurozone. For a market-centric economy like the United Kingdom (UK), the results may not hold. In fact, the ECB and the Bank of England (BoE) have differed on balance sheet composition and monetary policy intervention after 2008, as the BoE responded with greater quantities of bond purchases. Also, the interactions between agents in a different and more homogenous monetary financial system may lead to different conclusions. In this context, the previous model is replicated for the UK during the post-crisis period[21]. To ensure variable comparability, the data set starts in January 2010 and ends in September 2015. Stock market liquidity variables were retrieved by stocks currently listed on the FTSE 100.

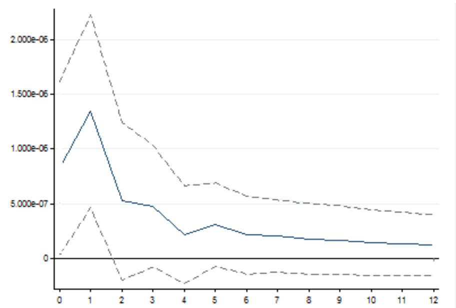
[21] Similar adjustments to variables and model validation tests were conducted, leading to a VAR (2) estimation, while first differences of CUR_DEP_UK, RES_DEP_UK, NCORE_UK, IPI_UK and IR_UK were taken to guarantee stationarity. Variable construction and relevant test results are reported in the Annex

Granger-causality test results are presented in Table 7, and confirm the hypothesis of causality between credit conditions and stock market liquidity for the UK, while proof for the hypothesis of reciprocal causality is less evident[22]. Accordingly, the IRFs plotted for significant causal relationships in Graphs 11-14 yield similar results relatively to the Eurozone. Positive innovations in the TED spread and the reserves-to-deposits are followed by increases in the Amihud illiquidity ratio in the short-term. Moreover, the reserves-to-deposits ratio growth has a negative impact on the turnover rate, while the TED spread widening raises the bid-ask spread during a more prolonged period. To conclude, it is interesting to notice that both the currency-to-deposits ratio and MFI non-core liabilities fail to impact any of the stock market liquidity dimensions. Provided the more market-oriented action of the BoE, the impact of both variables on stock market liquidity is found to be less significant.

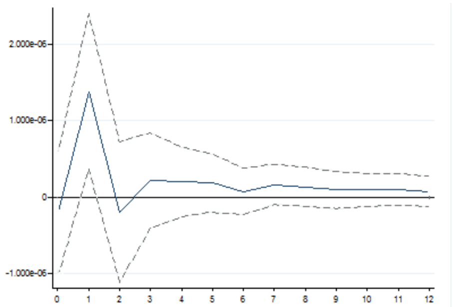
Graph 11 – Response of TO_UK to dRES_DEP_UK



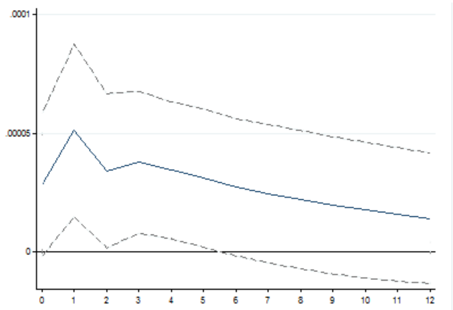
Graph 12 – Response of AMIHUD_UK to TED_UK



Graph 13 – Response of AMIHUD_UK to dRES_DEP_UK



Graph 14 – Response of BID_ASK_UK to TED_UK



Legend: ——— Orthogonalized IRF - - - - - - - 95% Confidence Interval Bands

[22] At a 5% significance level, only the bid-ask spread (BID_ASK_UK) is found to Granger-cause non-core liabilities (dNCORE_UK)

4. Conclusion

This paper examines the interplay relationship between the Central Bank and MFIs to determine credit conditions and the succeeding impact on stock market liquidity in the Eurozone from 2003 to 2015. In order to provide a fairly comprehensive picture of both concepts, several measures were integrated in the analysis and controlled for macroeconomic and financial variables. Further, the time span considered aims to enact the different behavior between agents during normal and turmoil periods. To test the model robustness, a similar procedure was conducted for a different monetary area, the UK.

The main results confirm the initial premise and can be summarized as follows. First, credit conditions represented by the interbank market sentiment, the monetary policy effectiveness and the MFIs financing structure jointly determine stock market liquidity. In fact, all IRF signs corroborate the hypothesis that easing credit conditions affect positively all dimensions of market liquidity. Second, evidence for the existence of liquidity spirals and bidirectional causalities is rather weak and only found at the money multiplier level. Third, even though the main results are verified for the UK, the impact of the currency-to-deposits ratio and the non-core liabilities is not statistically significant in this case.

This study leaves several doors open for future research. To start with, the impact of credit conditions on other asset markets (e.g. bond and derivatives markets) has yet to be investigated. Also, this relationship can be tested for European peripheral countries, particularly after the sovereign debt crisis. Bearing in mind the current transformations and challenges affecting financial markets, further analyses can incorporate the impact of regulations, capital standards and the increasing participation of high frequency traders. The possible existence of a flight-to-quality effect during the current QE program enacted by the ECB could also be assessed. Finally, an event study following the impact of ECB meeting decisions on both credit conditions and stock market liquidity may reinforce the results found.

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6. Appendix

Table 2 – Summary Statistics

	Observations	Mean	St. Deviation	Min	Median	Max
TO	153	0.005508	0.001038	0.003815	0.005367	0.010156
AMIHUD	153	0.000851	0.000886	0.000188	0.000525	0.006338
BID_ASK	153	0.004690	0.006385	0.001350	0.002768	0.058982
TED_EZ	154	0.003888	0.004601	-0.000300	0.002100	0.028200
dCUR_DEP	153	0.000221	0.000504	-0.002824	0.000227	0.002781
RES_DEP	153	0.027101	0.014807	0.000014	0.019581	0.077107
logNCORE	153	13.954049	0.126956	13.607562	14.013605	14.139865
MRET	153	0.004442	0.049959	-0.153848	0.012710	0.154600
MSTDEV	153	0.012732	0.006727	0.004862	0.011007	0.051116
dIR	154	-0.000149	0.002614	-0.011000	0.000000	0.008000
IPI	152	102.60342	8.580147	75.70000	103.25000	121.98000

Table 3 – Correlation Matrix

	TO	AMIHUD	BID_ASK	TED_EZ	dCUR_DEP	RES_DEP	logNCORE
TO	1.000						
AMIHUD	0.0392	1.000					
BID_ASK	0.0074	0.0812	1.000				
TED_EZ	0.4377	0.1300	0.2897	1.000			
dCUR_DEP	-0.0043	0.1480	0.0112	0.1181	1.000		
RES_DEP	0.0408	-0.0798	0.4695	0.3421	-0.0874	1.000	
logNCORE	0.2133	-0.6437	0.0967	0.4134	-0.2427	0.3405	1.000
MRET	-0.3782	-0.0937	-0.1320	-0.3391	0.0465	-0.0646	-0.1301
MSTDEV	0.5548	0.4464	0.1989	0.7582	0.2180	0.2625	0.1327
dIR	-0.0310	-0.1252	-0.0074	-0.2455	-0.0563	-0.1201	0.0173
IPI	0.3925	-0.1834	-0.0497	0.0138	-0.1427	-0.1578	0.1296

	MRET	MSTDEV	dIR	IPI
MRET	1.000			
MSTDEV	-0.4548	1.000		
dIR	0.0218	-0.2557	1.000	
IPI	-0.1019	-0.0295	0.1494	1.000

Table 4 – Augmented Dickey-Fuller Stationarity Tests

Variable / Null Hypothesis	**H_0: Unit Root**
Turnover Rate (TO)	-6.586*** (0.000)
Amihud Illiquidity Ratio (AMIHUD)	-4.012*** (0.001)
Effective Bid-Ask Spread (BID_ASK)	-5.895*** (0.000)
Eurozone TED Spread (TED_EZ)	-3.802*** (0.003)
Currency to Deposit Ratio (dCUR_DEP)	-11.344*** (0.000)
Reserves to Deposit Ratio (RES_DEP)	-3.379*** (0.012)

Note: P-values in parenthesis. *, ** and *** denote 10%, 5% and 1% significance level

Variable / Null Hypothesis	H_0: Unit Root
MFIs Non-Core Funding Liquidity (logNCORE)	-2.672* (0.079)
Stock Market Return (MRET)	-10.676*** (0.000)
Stock Market Standard Deviation (MSTDEV)	-4.919*** (0.000)
Inflation Rate (dIR)	-10.450*** (0.000)
Industrial Production Index (IPI)	-9.342*** (0.000)

Note: P-values in parenthesis. *, ** and *** denote 10%, 5% and 1% significance levels

Table 5 – VAR Order Selection Criteria

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4540.81				1.9e-35	-60.0775	-59.7921	-59.375
1	5184.9	1288.2	49	0.000	6.9e-39	-68.012	-67.3271*	-66.3261*
2	5239.15	108.5	49	0.000	6.4e-39	-68.082	-66.9975	-65.4126
3	5304.1	129.89	49	0.000	5.3e-39	-68.2946	-66.8105	-64.6417
4	5357.85	107.51	49	0.000	5.1e-39*	-68.358*	-66.4744	-63.7216
5	5403.35	91.008	49	0.000	5.6e-39	-68.3114	-66.0282	-62.6915

Note: * denote optimal values for each criterion

Table 6 – Lagrange-Multiplier Test for Residual Autocorrelation

Lag	Chi-Square Statistic	df	Prob. > Chi-Square Statistic
1	106.0072	49	0.00000
2	83.4792	49	0.00155
3	70.8867	49	0.02207
4	54.7008	49	0.26706

H_0: No autocorrelation at lag order

Table 7 – UK Model Granger-causality Tests

Credit Conditions	Market Liquidity		
	TO_UK	AMIHUD_UK	BID_ASK_UK
(i) – Credit Conditions (row) → Market Liquidity (column) H_0: Credit Conditions measure (row) does not Granger-cause the Market Liquidity measure (column)			
TED_UK	1.560 (0.458)	5.706* (0.058)	7.529** (0.023)
dCUR_DEP_UK	4.708* (0.095)	4.098 (0.129)	0.726 (0.695)
dRES_DEP_UK	8.546** (0.014)	12.134*** (0.002)	3.464 (0.177)
dNCORE_UK	0.193 (0.908)	n/a	2.304 (0.316)
(ii) – Market Liquidity (column) → Credit Conditions (row) H_0: Market Liquidity measure (column) does not Granger-cause the Credit Conditions measure (row)			
TED_UK	0.622 (0.733)	0.608 (0.738)	0.552 (0.759)
dCUR_DEP_UK	0.017 (0.992)	1.615 (0.446)	0.712 (0.700)
dRES_DEP_UK	1.164 (0.559)	1.795 (0.407)	3.826 (0.148)
dNCORE_UK	1.457 (0.483)	0.940 (0.625)	5.591* (0.061)

Note: P-values in parenthesis. *, ** and *** denote 10%, 5% and 1% significance levels